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Complacency and Intentionality in IT Use and Continuance

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Abstract

Decision makers' initial and continued use of information technology has traditionally been viewed as a mindful and intentional behavior. However, when a decision aid makes mostly correct recommendations, its users may become complacent. That is, users may accept recommendations without mindfully considering the recommendations or involvement with the aid. As such, they may be more likely to accept inaccurate recommendations. We draw on dual-processing theory to describe why users might behave in a mindless and complacent rather than mindful manner when using a decision aid. In our experimental investigation, we manipulated the accuracy of the recommendations provided by a decision aid and observe users' performance on a complex decision task. Using the decision aid, participants completed five task trials. To assess complacency and intentionality, we compared subjective (i.e., self-report) and objective (i.e., gaze data via an eye tracker) use measures. Our analysis and comparison of the subjective and objective responses indicate that, contrary to widespread theorizing, decision aid usage and continuance appear to be less intentional than commonly believed. Further, we found that a decision aid's users can be vulnerable to complacency even when recommendations are known to be inaccurate. Based on the findings of our study, we offer theoretical and practical implications regarding complacency and intentionality in technology use.

Keywords: IT Use, Complacency, Eye Tracking, Intentionality, Dual-Processing Theory.

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1. Introduction

Organizations derive significant benefit from deploying computerized decision aids to support employee decision making (e.g., McNab, Hess, & Valacich, 2011). However, along with these benefits can come drawbacks that undermine the sizeable investments firms make in such decision support systems. In many settings, decision aids are not always accurate, and users' unquestioning reliance on their recommendations can have major negative consequences, especially in critical contexts such as military applications, financial markets, or air traffic control (Parasuraman & Riley, 1997). Consider these three headlines:

- *Young people wrongly jailed because of computer error, court finds* (AAP, 2013)
- *Gate glitch traps a tanker in Piscataqua River* (McDermott, 2013)
- *Npower error cost my family a mortgage* (Blackmore, 2014)

In each case, reliance on a decision aid's recommendation resulted in humans taking incorrect action: numerous young people in Australia were wrongly imprisoned for violating bail because of incorrect information on the law enforcement computer system (AAP, 2013); an oil tanker was temporarily trapped in the Piscataqua River when the computer systems incorrectly reported that the bridge gates were open (McDermott, 2013); and a couple's mortgage application was rejected after their utility company's software incorrectly put a non-payment mark on their credit history (Blackmore, 2014). These cases and countless other anecdotes illustrate that, when individuals are not aware or mindful of their reliance on technology, such complacency can result in undesired outcomes. In this paper, we examine complacency by conducting an empirical study to observe individuals' objective and subjective reliance on a decision aid while they make complex decisions.

Complacency entails sub-standard monitoring of a decision aid (Parasuraman & Manzey, 2010) and occurs when individuals fail to observe or adequately assess the proper operation of a decision aid. It is most frequently observed in the form of individuals accepting recommendations from decision aids without questioning them (Parasuraman & Riley, 1997). If a decision aid obtains 100 percent accuracy, complacency is not an issue because reliance on such a system would yield perfect decisions every time. However, most decision aids perform imperfectly (Goddard, Roudsari, & Wyatt, 2012), and, therefore, require a human decision maker to oversee their operation. Therefore, complacency is a critical issue because it is the responsibility of human decision makers to synthesize the information supplied by the decision aid to make the ultimate decision.

Researchers have studied some post-adoption IS/IT use-related constructs that, on the surface, appear similar to complacency (e.g., IS habit, IS continuance, satisficing). A common theme across all of these constructs, including complacency, is that they concern post-adoption phenomena (Jasperson, Carter, & Zmud, 2005) that drive the continued and potentially automatic use of IS. However, complacency differs from the other constructs in terms of unintentionality and the potential negative consequences it can have. IS habit refers to "the extent to which people tend to perform behaviors (use IS) automatically because of learning" (Limayem, Hirt, & Cheung, 2007, p. 709). Habit encompasses subconscious behaviors that are inculcated automatically and differs from "experience" in the sense that it entails behavioral tendencies that are formed based on learned responses to a stable context (Limayem & Hirt, 2003) and requires weekly repetition of use at the minimum (Limayem et al., 2007). IS continuance refers to users' intention to continue using a certain IS (Bhattacherjee, 2001). Continuance is anteceded by users' satisfaction with the IS and its perceived usefulness. "Satisficing" (Simon, 1956), a concept that is similar to complacency, has also been studied in computer-aided decision making contexts, which refers to making acceptable but non-optimal decisions based on the available information (Newell & Simon, 1972), including raw data and/or decision aid recommendations. Decision aid users often tend to sacrifice decision accuracy for effort reduction (Payne, Bettman, & Johnson, 1993), which is easily achieved by (over)relying on the aid's recommendations.

There are three core features that define complacency (Parasuraman & Manzey, 2010) and also distinguish it from habit, continuance, and satisficing: first, it involves human monitoring of an automated system. Second, such monitoring occurs less often than what is standard or optimal and, thus, is considered “substandard”. Third, there is a direct and observable effect on system performance (i.e., the setting in which the recommendations of a decision aid are enacted) as a result of substandard monitoring. While complacency only applies in automation or recommendation-based decision making contexts, habit and continuance apply to the use of IS in general and may not necessarily involve the monitoring of the IS. Both habit and continuance are a result of conscious satisfaction in using or interacting with the IS, regardless of the need of human monitoring. For instance, they have been observed in the contexts of Internet use (Limayem et al., 2007), online banking (Bhattacherjee, 2001), and the use of Internet-based communication tools (Limayem & Hirt, 2003). All of these contexts involve interaction with an IS and the formation of (repeated) usage behaviors without the need for human operators to monitor any information or make any decisions for the IS to function. Complacency, on the other hand, only applies to decision making contexts where there is a consistent need for monitoring, and it develops because the inaccuracies of the IS are *unintentionally* dismissed due to substandard monitoring. Satisficing similarly applies in recommendation-based decision making contexts but differs from complacency in that it is not a result of unintentional substandard monitoring and that satisficing users may *intentionally* sacrifice accuracy in an attempt to spend less effort while achieving an acceptable performance level (Payne et al., 1993). Furthermore, complacency implies direct, undesired, and unforeseen *negative* effects on system performance, whereas habit, continuance, and satisficing form based on users’ *positive* experiences or expectations regarding performance improvements (Bhattacherjee, 2001; Limayem & Hirt, 2003) or effort reduction (Paquette & Kida, 1988). Accordingly, complacency research almost exclusively focuses on the negative consequences of IS use regarding economic, safety, or performance outcomes (Parasuraman & Manzey, 2010), while such consequences of IS use have not been studied extensively in the contexts of habit, continuance, or satisficing.

Despite the potential for complacency, the MIS literature has traditionally conceptualized individuals’ technology use intentions as mindful actions; that is, the result of rational decision making (e.g., the technology acceptance model (TAM) (Davis, 1989) or the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003)). The theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB) (Ajzen, 1991) underlie both TAM and UTAUT. Both theories conceptualize human behavior as intentional and mindful; as such, technology use has also been viewed as intentional and mindful. However, other related literatures, including psychology, suggest that technology use might be more automatic and less intentional than the MIS literature has typically argued (Ortiz de Guinea & Markus, 2009). Therefore, investigating technology use through intentions or similar self-reported metrics, which presumes that individuals are aware (i.e., mindful) of their actions, may have resulted in an incomplete understanding of IT usage. Note that some past MIS research has shown that individuals’ actual IT usage can be quite different from their perceived (i.e., self-reported) usage (Straub, Limayem, & Karahanna-Evaristo, 1995).

We investigate the development of complacency in the context of a complex decision making task (i.e., stock purchasing). To better understand complacency, we conducted an exploratory empirical study for which we “develop[ed] [new] instrumentation … to measure the cognitions and use behaviors associated with … post-adoptive behavior” as previous research has suggested (Jasperson et al., 2005, p. 548). Specifically, we observed the extent to which decision makers engaged in verification efforts by collecting objective measures via an eye tracker under different levels of decision-aid accuracy. We also examined how complacency was reflected in decision makers’ self-reported trust and reliance on the decision aid. To avoid limiting our ability to detect findings in this initial investigation, we report as significant all findings at or below alpha = 0.10.

Our findings contribute to the understanding of technology use in three broad avenues. First, our results suggest that the assumptions of rational or mindful use might not always hold. Second, they help explain how and when complacency and intentionality occur, which constitutes the first step in mitigating the misuse, disuse, and abuse of decision aids (see Parasuraman & Riley, 1997). Third, they uncover the effects of a decision aid’s accuracy on its users’ reliance on the aid, which helps recognize the consequences and implications of inaccuracy in decision aids, especially with regards to intentionality and complacency. Our theoretical contribution to the IS/IT use literature lies in elucidating the automatic and mindless nature of users’ continued reliance on decision aids because we provide empirical support for the arguments of Ortiz de Guinea and Markus (2009) regarding unintentionality in technology use.

2. Theoretical Development

To frame our investigation of complacency, we build on dual processing theory (Kahneman, 2011), which argues that individuals have two distinct approaches (i.e., system 1 and system 2) to cognitive processing. System 1 is always active and continuously processes large amounts of information without our conscious awareness or intention. Perhaps developed as an evolutionary safety mechanism, system 1 allows humans to make quick and effortless decisions based on environmental stimuli, such as the decision to avoid or approach a potential incoming threat. When relying on system 2, humans carefully weigh information before reaching a conclusion to make relatively more thoughtful and accurate decisions. System 2 requires considerable attention and cognitive effort, which humans have a strong tendency to conserve (Payne, Bettman, & Johnson, 1993); hence, it must be intentionally activated. Thus, individuals make many daily and regular decisions via system 1 while reserving system 2 only for novel, important, or complex decisions (Kahneman, 2011).

This tradeoff between system 1 and system 2 (low vs. high effort) echoes other cognitive information processing theories, such as the elaboration likelihood model (ELM) (Petty & Cacioppo, 1986a, 1986b) and the heuristic-systematic model of information processing (HSM) (Chaiken, 1980, 1987). A common theme in all of these theories is that an individual can either carefully and thoroughly consider information before making a decision or make a decision using superficial heuristics, which essentially serve as mental shortcuts (Eagly & Chaiken, 1993; Petty & Cacioppo, 1986a, 1986b; Tam & Ho, 2005). The notion that humans may sacrifice accuracy to conserve cognitive effort is emblematic of how individuals process information in their daily lives and make decisions, be they simple or complex. Table 1 presents a brief overall comparison of system 1 versus system 2 (see also, Kahneman, 2011).

Table 1. Brief Summary of the Dual Processing Theory

	System 1	System 2
Decision mechanism	Snap judgment / Intuition	Careful consideration
Activation mechanism	Automatic / Always On	Intentional
Effort level	Easy and effortless	Tiring and effortful
Decision characteristics	Fast and efficient	Careful and good judgment
Decision outcome	Mostly biased	Mostly critical

Consistent with the above argument, research investigating computer-aided decision making has also found evidence of system 1 and system 2 decision making. Providing supplementary cues (i.e., heuristics) to emergency response dispatchers improved dispatchers' information selections and processing performance while decreasing their response time (McNab et al., 2011). Further, these cues were observed to be more beneficial under increased time pressure and task complexity. Note, however, that the cues provided by the decision aid were always accurate. The findings of this research and other similar research in different contexts such as credibility assessment or online shopping (e.g., Jensen, Lowry, Burgoon, & Nunamaker, 2010; Reisen & Hoffrage, 2010) point to the importance and effectiveness of supporting heuristic processing in complex decision making tasks. However, in many circumstances, it is impossible to develop a decision aid that always provides perfectly accurate recommendations. Hence, other research highlights the dangers of promoting system 1 processing because imperfect heuristics or inaccurate cues can result in biased or inaccurate decisions (e.g., Allen & Parsons, 2010; Meservy, Jensen, & Fadel, 2013).

3. Complacency and Intentionality

When individuals encounter a novel situation, such as using a new decision aid of unknown function and reliability, they are likely to first approach it cautiously to determine if it merits consideration during the decision making process. Due to its novelty, individuals are likely to examine and test the performance of the unfamiliar decision aid carefully (i.e., via system 2) until they become familiar with the aid.

Over time, as individuals develop experience with the decision aid, they are likely to obtain a sense of its accuracy with which they develop an opinion about the function and reliability of the aid's recommendations. Given that individuals tend to conserve cognitive effort (Payne et al., 1993), the effortful, careful, and intentional consideration of the decision aid's performance (via system 2) is likely to diminish over time. Instead, users are likely to rely on simple heuristics to govern their use of a decision aid. Put differently, over time, system 1 will begin to dominate individuals' interactions with the decision aid to replace the careful consideration supported by system 2 reasoning. Such a shift can occur seamlessly and rapidly because system 1 always runs in the background and can suggest actions based on impressions and intuitions of the aid. In turn, users can easily adopt such suggestions and, thus, return to the default low-effort mode of decision making (Kahneman, 2011). Thus, individuals' use and continuance behaviors are expected to evolve such that they naturally shift to a reliance on simple heuristics and mental short cuts, seeding individuals for the development of complacency.

Complacency arises, then, as individuals abdicate their responsibility for decision making and blindly accept the recommendation of the decision aid without verifying the aid's recommendation. If the decision aids were infallible, complacency would not be a danger, but few decision aids can guarantee complete accuracy. In addition, complacency is more likely when a decision aid is highly, but imperfectly, reliable (Parasuraman, Molloy, & Singh, 1993). In such cases, the probability of users detecting an inaccurate recommendation decreases steadily and significantly over time (Molloy & Parasuraman, 1996). Hence, we anticipate recommendation verification efforts to decrease over time regardless of decision aid accuracy. Further, other work suggests that users' monitoring performance declines as recommendation reliability becomes constant (Parasuraman et al., 1993). Thus, we expect the users of a highly reliable decision aid to accept its recommendations increasingly easily and, thus, spend less time and attention on the raw information related to the task or assessing the correctness of the decision aid's recommendations.

> **H1:** A user spends less effort verifying a decision aid's recommendations as their number of usage trials increases.
>
> **H2:** Higher decision aid accuracy is associated with a decrease in users' recommendation verification efforts as their number of usage trials increases.

As individuals become accustomed to a decision aid and rely on its recommendations, we can expect their usage pattern with the decision aid to change. Past work has shown that abnormal or unexpected decision aid actions (e.g., erroneous recommendations) have a negative impact on the trust users place in the decision aid and their future usage intentions (Komiak & Benbasat, 2006). However, we argue that this decrease in trust and anticipated usage may diverge from actual usage behaviors. The heuristics that drive our actions under system 1 are often formed and applied outside of conscious thought (Kahneman, 2011). Thus, while individuals may be aware that recommendations from a decision aid are only partly trustworthy, they can accept and implement the recommendations regardless. Inaccurate decision aid recommendations may not be sufficient to prevent users from employing a quick heuristic approach by relying on the advice offered by the decision aid. Evidence for this concept has been observed where individuals' self-reports of their use intentions and actual usage behaviors significantly differ, indicated by the lack of correspondence between self-reported and computer-recorded technology (i.e., voice-mail) use (Straub et al., 1995). In fact, usage intentions only accounted for a third of the variance in actual use even when, for example, the most desirable and accurate self-report measures were used (Kim & Malhotra, 2005). Similarly, a nomological net analysis that Straub et al. (1995) performed suggests that IT use can be factored into two independent subconstructs (i.e., actual usage and self-reported usage), possibly with different antecedents and/or consequences. Based on these results, they called for future research to examine the lack of correspondence between these subconstructs and suggested modifying the theoretical basis of TAM by reformulating the dependent variable as the perceived system use rather than actual use.

As we note earlier, recent arguments suggest that using decision aids may be much less intentional and more automatic than previously assumed (Ortiz de Guinea & Markus, 2009), which, together with dual-processing theory, can help explain the divergence between self-reported (i.e., perceived) and actual usage of technology. If system 1 becomes more influential on decision aid use over time as we argue, it is likely that users will continue to employ the recommendations of a decision aid even when their perceived usage and usage intentions decrease due to the perceived inaccuracy of the aid. This occurs because their actual usage is driven mostly by their automatic and subconscious tendency to conserve cognitive effort and attention, whereas their perceived usage might decline in conjunction with their trust in the system. Lee and Moray (1992) observed this phenomenon in an empirical study. They conclude that "operators' use of automatic controllers depends upon more than trust alone" (p. 1268) after finding that chronic faults by a decision aid led to increased use together with decreased trust. Previous research also suggests that perceived reliability, trust, usage intentions, and self-reported technology use are closely related (Fishbein & Ajzen, 1975; Komiak & Benbasat, 2006; Pavlou, 2003). Further, actual and self-reported technology use can vary significantly (Kim & Malhotra, 2005; Straub et al., 1995). Thus, collective empirical evidence suggests that the accuracy of a decision aid can differentially affect actual usage in contrast to trust and perceived usage. In short, when a decision aid provides inaccurate recommendations to a "cognitive miser", it is entirely possible for the perceived (i.e., conscious) and actual (i.e., subconscious) dimensions of usage to differ significantly if technology use is not completely intentional as we argue. Thus, as a test of intentionality in decision aid use, we propose:

> **H3:** The effect of decision aid accuracy on self-reported (a) trust and (b) usage is stronger than its effect on (c) actual use behaviors.

4. Method

4.1. Overview

To investigate our hypotheses, we conducted an experimental simulation in which participants viewed information about stocks and made purchase (buy/no buy) decisions. We developed a financial decision aid for this purpose (Figure 1). The aid provided participants with raw information about a stock (on the left side of Figure 1): previous years' prices, comments from financial analysts, and recent headlines from mass media. In addition, the tool provided a prediction of the future stock prices and a recommendation (buy/no buy) along with its basis (on the right side of Figure 1). We dichotomously varied the accuracy of the decision aid's recommendation between participants. Each participant was randomly assigned to one of the two accuracy treatments (i.e., high or low accuracy) and repeated the stock purchasing task five times. After each decision (buy/no buy), the aid provided immediate feedback to the participant about the action of the stock price. Hence, participants had immediate knowledge about the accuracy of the aid after each decision.

An eye tracker (see Section 4.3.2 for details) recorded participants' eye movements to understand their actual use of the information displayed by the decision aid. Additionally, by comparing participants' self-reported trust in the decision aid and future use intentions with their actual acceptance of the decision aid's recommendation, we assessed participants' intentionality during use.

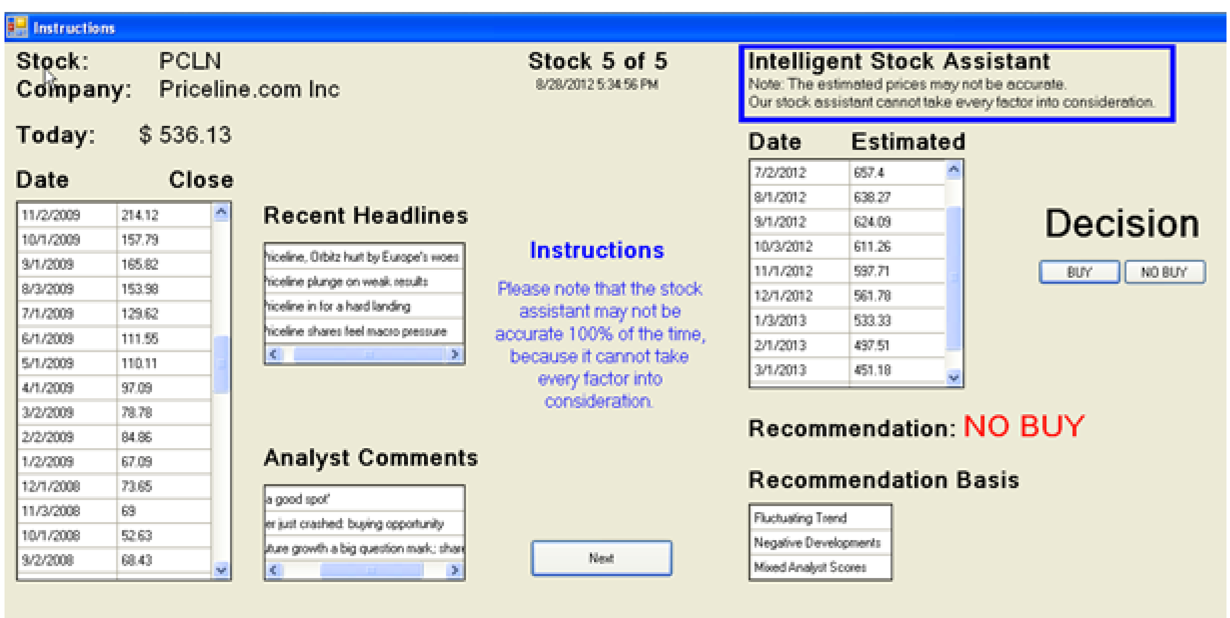


Figure 1. Financial Decision Aid

4.2. Participants

A sample (n = 29) of graduate and undergraduate students participated in this experiment. Due to the nature of collecting and interpreting eye tracker data, similar sample sizes are common for data collections at a single location (e.g., the sample sizes in Cyr, Head, Larios, & Pan (2009) and Djamasbi, Siegel, Skorinko, & Tullis (2011) were 22 and 30, respectively). We recruited participants from a business college at a large Mid-Western university. These students were, on average, 22.5 years' old, and 64.3 percent were male. Participants received extra credit to encourage participation worth approximately 1 percent of their grade. We excluded one participant's eye tracking data due to excessive movement that rendered the participant's gaze untrackable. Thus, the effective sample size was 28.

Participants were enrolled in a financial modeling class that addresses stock valuation in detail. We began recruiting participants after the in-class instruction and exercises regarding stock valuation were completed. Therefore, all participants were familiar with the stock valuation task. Since we focused on how the participants interacted with the decision aid (i.e., their intentionality and complacency) rather than their actual stock valuation performance (which was not evaluated in our experiment), we believe that their informed familiarity with the topic qualified them as potential users of a similar financial decision aid and, hence, as legitimate participants in our experiment. Student participants with similar levels of familiarity have been commonly used in other financial decision making studies (e.g., Hirst, Koonce, & Simko, 1995; Libby, Bloomfield, & Nelson, 2002; Peterson, 2001). Thus, we expected students' familiarity with our experimental context to be sufficient for this study and the effects of sampling students to be minimal (see DeSanctis, 1988). Nevertheless, we measured task familiarity and included it as a control variable.

4.3. Measurement

4.3.1. Independent Variable—Accuracy

We dichotomously manipulated the accuracy of the decision aid between subjects such that it was either completely accurate (i.e., 5/5 correct recommendations) or mostly inaccurate (i.e., 2/5 correct recommendations; only the second and fifth recommendations were correct, and the first, third, and fourth recommendations were incorrect). We refer to these experimental conditions as the "high accuracy" and the "low accuracy" conditions, respectively. Each participant received only one of the two accuracy treatments. We selected two of five correct recommendations for the low-accuracy condition rather than five inaccurate recommendations because a consistently wrong decision aid could be considered highly accurate, only in the wrong direction. In such a setting, it would be possible for participants to consistently select the opposite of the aid's recommendations and have perfectly accurate decisions. Such an approach would essentially make the decision aid reliable and confound our results. Thus, we designed the decision aid to make occasionally correct recommendations. We assessed the effectiveness of this manipulation via two seven-point Likert-type items ("The decision aid was accurate", "The decision aid's recommendation was correct") after the participants completed the five trials. We performed the manipulation checks after the participants completed all trials, rather than after each trial, to prevent potential priming effects. Asking the participants to consider the accuracy or correctness of the decision aid's recommendation after each trial could have primed them to be suspicious of the recommendations or to expect the decision aid to be consistently accurate or inaccurate, either of which could have confounded our results. Comparing the responses of the participants in the two conditions (high vs. low accuracy) revealed a statistically significant difference ($p<0.001$) for both items (see Table 2). Hence, we deemed our manipulation of decision aid accuracy to be effective.

4.3.2. Dependent Variables—Complacency

We used a Tobii TX-300 eye tracker with a 300 Hz sampling rate to capture participants' verification efforts. Other researchers have used similar eye trackers from the same manufacturer to examine individuals' information browsing behaviors, such as reading expert opinions on a webpage (Djamasbi, Siegel, & Tullis, 2012) or simply browsing e-commerce sites to select products (Sheng & Joginapelly, 2012). We collected two types of data via the eye tracker: view time and fixation count.

View time is a measure of the time a participant spends looking at a given area on their screen. Greater time spent viewing an area is consistent with greater cognitive effort or verification (Parasuraman & Manzey, 2010). To capture these data, the experimenter identifies areas of interest (AOIs) on the computer monitor. The specific AOIs defined for this experiment were the portion of the screen that displayed the raw information about the particular stock (see the left hand side of Figure 2) and the portion of the screen that provided the information from the decision aid (see the right hand side of Figure 2). These data provided our measure of how much time each participant spent gazing at the raw information about a stock versus the decision aid's estimation and recommendation.

Fixation count indicates the number of times a participant fixated their gaze on a given area of the screen. Consistent with view time, higher fixation counts are indicative of higher levels of cognitive effort or verification. Based on the AOIs described above, we recorded how many times a participant focused on the raw information (displayed on the left hand side) about a stock versus the decision aid's estimation and recommendation (provided on the right hand side).

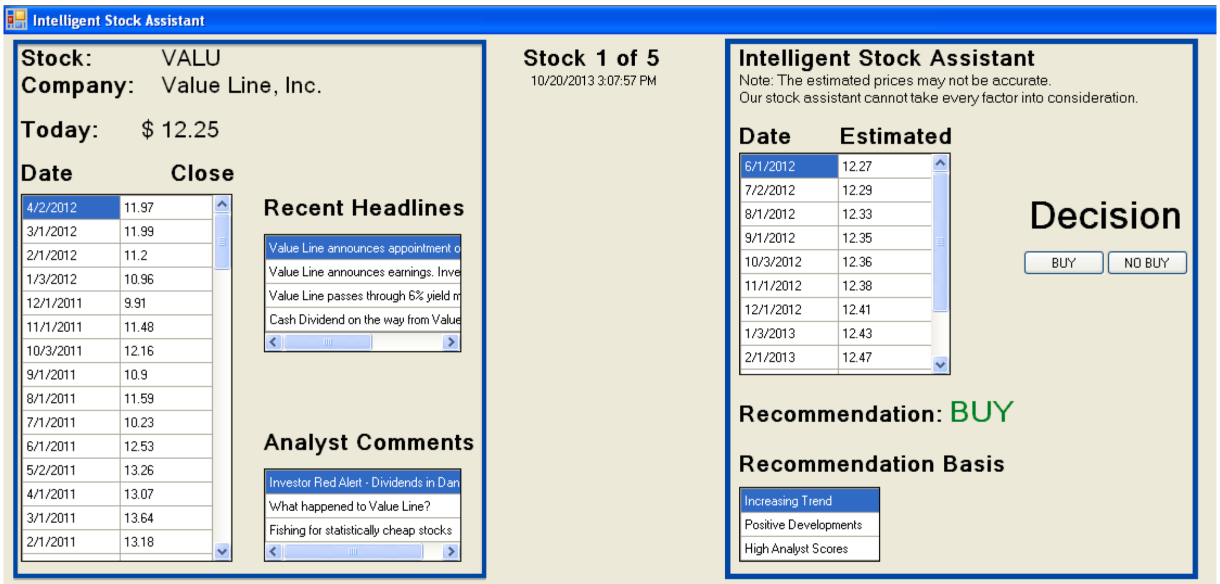


Figure 2. Areas of Interest (AOI) for the Financial Decision Aid (Raw Information AOI: Highlighted Above on Left; Decision Aid AOI: Highlighted Above on Right)

Researchers have measured complacency as the extent to which users verify a decision aid's recommendation (Bahner, Hüper, & Manzey, 2008). When non-complacent users notice a wrong or suspicious recommendation, they take more time to process available information as they consider the recommendation (Manzey, Reichenbach, & Onnasch, 2008). Hence, spending a relatively longer time on a decision task is an important characteristic of non-complacent decision making. Conversely, relying on heuristics inherently speeds up the overall decision making process (Kahneman, 2011). As such, complacent users spend less time making buy/no buy decisions. Further, the development of complacency would be evident when consecutive decisions are accomplished at a faster rate (i.e., later decisions take less time than earlier ones due to less effort spent verifying recommendations). In this study, therefore, we associate complacency with a decreasing view time and fixation count for either the decision aid or the raw information areas over task trials.

4.3.3. Dependent Variables—Intentionality

We measured use intentions via four survey items (adapted from Hayes, 2006) that captured participants' perceptions of their reliance on the decision aid and their intentions to rely on it in the future (Appendix A (point 1)). We combined the responses (Cronbach's Alpha = 0.83) into a mean score of use and continuance intentions.

To assess participants' trust in the decision aid, they responded to seven survey items (adapted from the Jian, Bisantz, & Drury, 2000 study of trust in decision aids; Appendix A (point 2)). We combined the responses (Cronbach's Alpha = 0.86) to create a mean score of trust.

We recorded recommendation acceptance as an objective measure of the participants' reliance on the decision aid. Specifically, participants' agreement with the decision aid's recommendation was recorded after each stock purchase decision. When a participant's decision (buy/no buy) agreed with the recommendation, a code of 1 was assigned; if not, a code of 0 was assigned. We converted these values into an average agreement score (in percentage) to measure complacency. For instance, if only 3 of a participant's decisions matched with the respective recommendations of the decision aid, we calculated that individual's average agreement score to be 60 percent (3/5).

4.3.4. Control Variable—Task Familiarity

Despite participants' familiarity with stock valuation, we wished to rule out the alternative explanation that participants' knowledge and experience in the specific context influenced their reliance on a decision aid in that context. Therefore, we asked the participants about their previous experience with buying stocks. We asked participants to self-report their familiarity with buying stocks by responding to two survey items (adapted from a study of task analysis by Adams, 2010; Appendix A (point 3). We combined the responses (Cronbach's alpha = 0.74) to form a mean score of task familiarity.

5. Procedures

During recruitment, we informed each participant that they would view some information about stocks and be asked to make purchase (buy/no buy) decisions based on their prediction of the future performance of the stocks. The participants individually came to a laboratory where they were verbally briefed by the experimenter (following a script) about the nature of the experiment, was given the chance to ask questions, and gave consent. We randomly assigned each participant to an experimental condition (i.e., high or low accuracy). Then, we seated the participant in front of a computer monitor equipped with an eye-tracking device, similar to a large webcam. To capture view time and fixation count, the eye tracker must first be calibrated to each participant. To accomplish this, after participants were seated in front of the computer, we asked them to follow a red circle that moved around on the screen with their eyes. Following calibration, data collection began as the experimenter left the room and the instruction and training phase commenced.

The purpose of the instruction and training phase was to ensure that participants understood the experimental instructions and were familiar with the experimental process prior to the actual experiment. Such training is particularly important for studies in which participants repeat a task (e.g., McNab et al., 2011; Shaft & Vessey, 1995) to prevent potential confounds with the learning effects associated with repeated use. Therefore, we walked each participant through a practice stock purchase decision. The nine-step instruction process visually and narratively guided the participants through making a stock purchasing decision and highlighted all of the information available on the decision aid. During each instruction step, a portion of the screen was highlighted, and detailed instructions relevant to the highlighted area were provided at the middle of their screen (see Figure 1). We instructed each participant to interact with the decision aid as they would in the actual experiment. During the instruction and training phase, we advised the participants that the decision aid's recommendations might not be perfectly accurate. Further, a notice stayed on the screen for the duration of the experiment (highlighted at the top right corner in Figure 1). At the end of the training phase, the participants were instructed to call the experimenter if they required any clarification. None required additional explanation.

As the participants performed the experimental task for each of the five different stocks, the eye-tracker recorded their gaze to obtain view times and fixation counts. We randomly chose the stocks used in the experiment, and the information, prices, and future price estimations presented to the participant were fictional. When the participant made a decision, a feedback message appeared that indicated if the price of the stock increased or decreased, consistent with the trend in the raw information provided to the participants. Hence, the direction of each stock's price was consistent with the raw data presented to the participant. Participants had unlimited time to complete the five trials, for which they took an average of seven minutes and two seconds. After each participant completed all five decisions, the eye tracker was turned off and the participant was asked to respond to an online survey containing the items regarding use intentions, trust, and task familiarity (Appendix A) before being excused. Prior to the main experiment, we conducted a pilot study with three doctoral students. Based on their experiences, we deemed that no changes to the decision aid or experimental procedures were necessary.

6. Results

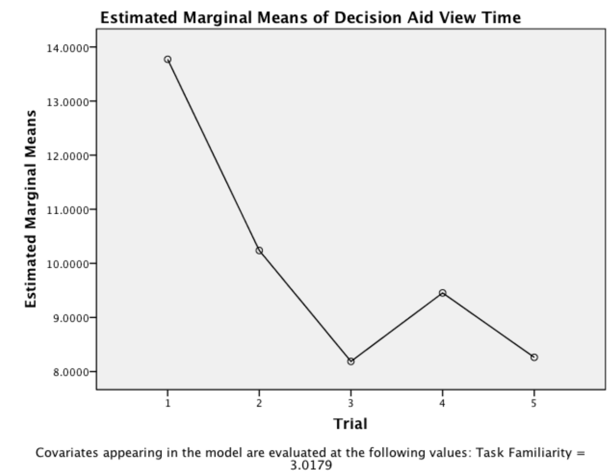
We conducted two distinct analyses with the complacency and intentionality variables. Table 2 presents the descriptive statistics for all variables. Because of the relatively small sample size and new instrumentation (developed as suggested by Jasperson et al., 2005) used in this exploratory study, we report all effects that approached conventional levels of statistical significance (p<0.10).

Table 2. Descriptive Statistics

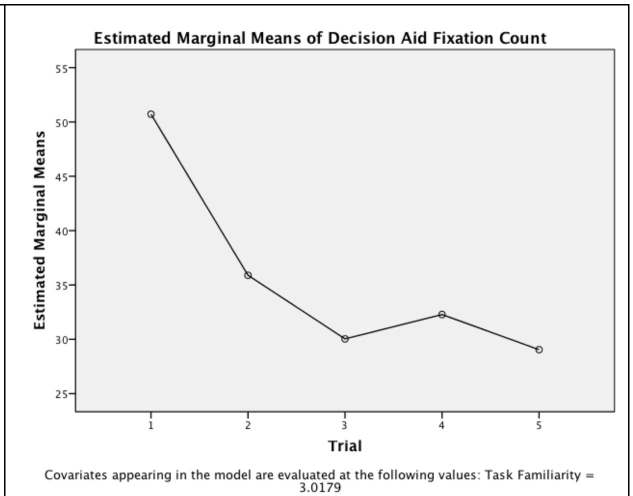
Variables		Experimental condition	
Complacency variables		**Low accuracy**	**High accuracy**
		Mean (St. Dev.)	Mean (St. Dev.)
Raw information view time	Trial 1	33.92 (15.49)	43.15 (23.62)
	Trial 2	32.21 (19.39)	36.04 (22.21)
	Trial 3	33.48 (17.97)	28.89 (13.78)
	Trial 4	39.50 (32.22)	29.63 (17.02)
	Trial 5	24.17 (19.25)	28.94 (19.52)
Raw information fixation count	Trial 1	107.00 (34.01)	126.53 (57.91)
	Trial 2	97.31 (50.62)	105.53 (62.92)
	Trial 3	100.85 (48.80)	90.93 (38.71)
	Trial 4	110.46 (82.53)	91.67 (47.56)
	Trial 5	78.69 (57.94)	90.93 (50.78)
Decision aid view time	Trial 1	11.37 (4.29)	16.18 (11.71)
	Trial 2	10.39 (7.08)	10.06 (5.46)
	Trial 3	8.39 (5.85)	7.97 (6.75)
	Trial 4	11.38 (10.79)	7.54 (7.77)
	Trial 5	6.91 (6.42)	9.58 (7.78)
Decision aid fixation count	Trial 1	43.85 (15.45)	57.60 (37.55)
	Trial 2	36.69 (21.04)	35.00 (14.82)
	Trial 3	32.31 (20.40)	27.73 (21.03)
	Trial 4	40.92 (38.74)	23.67 (14.17)
	Trial 5	24.54 (20.68)	33.47 (22.05)
Recommendation acceptance	Trial 1	0.69 (0.48)	0.40 (0.51)
	Trial 2	0.77 (0.44)	0.60 (0.51)
	Trial 3	0.31 (0.48)	0.73 (0.46)
	Trial 4	0.54 (0.52)	0.80 (0.41)
	Trial 5	0.77 (0.44)	0.93 (0.26)
Intentionality variables		**Low accuracy**	**High accuracy**
		Mean (St. Dev.)	Mean (St. Dev.)
Use		3.25 (0.95)	4.28 (1.22)
Trust		3.00 (0.63)	4.97 (0.77)
Mean recommendation acceptance		0.62 (0.15)	0.69 (0.17)
Control variable		**Low accuracy**	**High accuracy**
		Mean (St. Dev.)	Mean (St. Dev.)
Task familiarity		2.88 (1.50)	3.13 (1.27)
Manipulation checks		**Low accuracy**	**High accuracy**
		Mean (St. Dev.)	Mean (St. Dev.)
"The decision aid was accurate"		3.15 (1.21)	6.67 (1.05)
"The decision aid's recommendation was correct"		2.77 (1.09)	6.80 (0.78)

To investigate complacency, we fit a repeated-measure analyses of covariance (Repeated ANCOVA) model for each dependent variable. For each model, the accuracy of the decision aid (i.e., low or high accuracy) was entered as a between-subjects variable, trial (i.e., the series of purchasing decisions for stocks 1-5) as a within-subjects variable, and the complacency measures (i.e., view time and fixation count for the raw information AOI and the decision aid AOI) as the dependent variables. Task familiarity was entered as a covariate into all of the models. Among these four models, we observed three significant effects (Appendix B): The main effects of trial on decision aid view time ($F(4,100) = 2.070$, $p = 0.090$) and fixation count ($F(4,100) = 2.101$, $p = 0.086$) and the interaction effect of trial and accuracy on raw information view time ($F(3.541,88.521) = 2.287$, $p = 0.074$). These results support H1 and H2. Figure 3 depicts each of these effects.

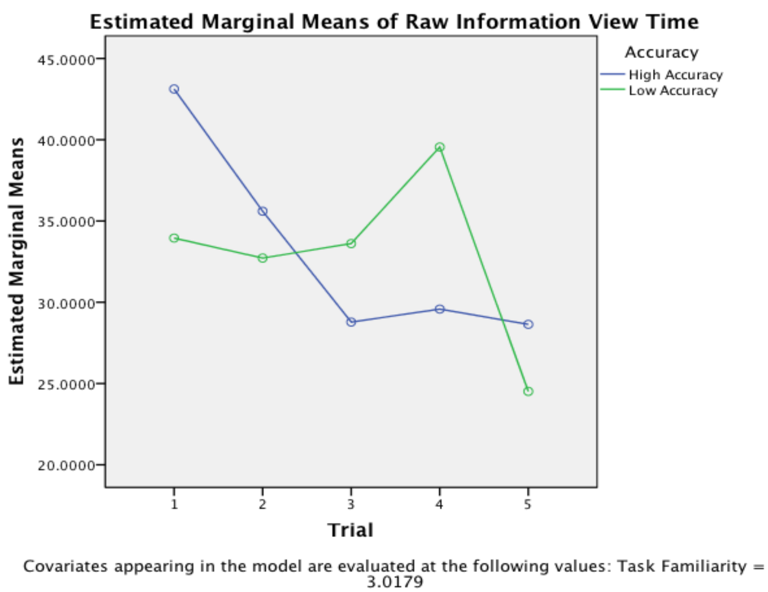
Consistent with our expectations from H1, the main effects of trial on decision aid view time and fixation count (Figures 3(a) and 3(b)) indicate that participants spent increasingly less time scrutinizing the decision aid's estimates and recommendation as the experiment progressed. However, the main effect for trial was limited to the time spent viewing the decision aid; we did not observe a trial effect on the fixation count or view time for the raw information.



a. Trial on decision aid view time



b. Trial on decision aid fixation count



c. Trial * accuracy on raw information view time

Figure 3. Significant Effects from Repeated ANCOVAs

Nevertheless, participants in the high-accuracy condition spent increasingly less time looking at the raw information as they progressed (Figure 3(c)). This finding, coupled with the increasing acceptance of the decision aid's recommendations (Table 2), clearly illustrates complacency developing for participants in the high-accuracy condition. This finding is consistent with H2, suggesting that accuracy increases the rate at which complacency develops. However, accuracy was not observed in a significant interaction effect influencing the view time or fixation count for the decision aid.

In considering these two findings together, we surmise that repeated trials were sufficient to reduce the amount of attention and scrutiny (i.e., recommendation verification efforts) directed at the decision aid. But we observed high accuracy, in addition to repeated trials, to further reduce the attention and scrutiny directed at the raw information.

To examine intentionality (H3), we ran a multivariate analysis of covariance (MANCOVA) using the mean recommendation acceptance and the self-reported use and trust measures as the three dependent variables. Consistent with the previous analysis, accuracy was modeled as a between-subjects variable with task familiarity as the covariate (Table 3). Accuracy had a significant multivariate effect on the DVs (Pillai's Trace = 0.763, $F = 23.571$, $p < 0.001$). The models for trust ($F(2,24) = 27.117$, $p<0.001$) and self-reported use ($F(2,24) = 5.448$, $p = 0.011$) were both significant, with adjusted R-squares of 0.668 and 0.255 and partial eta-squares of 0.693 and 0.312, respectively. The model for recommendation acceptance was not significant ($F(2,24) = 1.333$, $p<0.282$).

According to the univariate, between-subjects tests, participants in the low-accuracy condition (mean = 3.007, s.d. = 0.195) trusted the decision aid less than the participants in the high-accuracy condition (mean = 4.963, s.d. = 0.188) did ($F(1,24) = 52.315$, $p<0.001$). Furthermore, the participants in the low-accuracy condition (mean = 3.258, s.d. = 0.276) reported using the decision aid less than the participants in the high-accuracy condition (mean = 4.457, s.d. = 0.266) ($F(1,24) = 9.666$, $p<0.005$). However, we did not detect a significant difference in recommendation acceptance for the high accuracy (mean = 68.7%, s.d. = 4.5%) and low accuracy (mean = 61.4%, s.d.= 4.3%) conditions. In other words, average agreement with the decision aid was not significantly different between the low accuracy and high-accuracy conditions, unlike the self-reported use/continuance and trust. This pattern of behavior (i.e., agreement with tool) and self-report supports H3.

As a robustness test for H3, we reran the MANCOVA using the mean recommendation acceptance for only the first, third, and fourth trials (i.e., only the inaccurate recommendations in the low-accuracy condition) instead of the mean recommendation acceptance for all trials, which produced similar results. The model for recommendation acceptance ($F(2,24) = 1.434$, $p<0.258$) and the difference between the recommendation acceptance for the high accuracy and low-accuracy conditions were still not statistically significant.

7. Discussion

The results of our study confirm that a decision aid, when highly accurate, provides many beneficial properties; its users trust its recommendations, find it useful, and indicate a willingness to rely on it in the future. Along with these beneficial properties, however, we observed some important issues that could negatively affect individuals' interaction with a decision aid and users' decision quality. Below, we discuss our results and main findings.

The overall results reveal a consistent overall decline in recommendation verification efforts (i.e., all four eye tracking measures) over time across both treatments (see Table 2). Note that this decline was particularly sharp for the last (i.e., fifth) trial in the low-accuracy condition; compared to the previous (i.e., fourth) trial, raw information view time decreased 39 percent, raw information fixation count decreased 29 percent, decision aid view time decreased 39 percent, and decision aid fixation count decreased 40 percent. In contrast, this drop off in view times and fixation counts was accompanied by a 43 percent increase in average recommendation acceptance (i.e., .54 to .77). We argue that this trend serves as a vivid example of complacency because it demonstrates a substantial overall decrease in recommendation verification efforts coupled with an equally substantial increase in recommendation acceptance even though we provided the participants with two consecutive incorrect recommendations for prior (i.e., third and fourth) trials. In other words, the participants were more in agreement with the decision aid's recommendation and less questioning of it after having received two incorrect recommendations in a row. Although we observed a general declining pattern in recommendation verification efforts, the amount of decline was not always consistent as evidenced by the particularly sharp decline for the fifth trial. These findings suggest that the onset of complacency may develop rather abruptly after a certain threshold of trials has been reached. We call for future research to investigate this potential threshold effect and the factors (e.g., decision context or complexity) that might influence this threshold and hence the pace of complacency.

Table 3. MANCOVA Between-Subject Effects

Source	Dependent variable	Type III sum of squares	Df	Mean square	F	Sig.	Partial eta squared	Observed power
Corrected model	Use	10.787	2	5.393	5.448	.011	.312	.884
	Trust	26.702	2	13.351	27.117	.000	.693	1.000
	Recommendation acceptance	.069	2	.034	1.333	.282	.100	.382
Intercept	Use	53.153	1	53.153	53.692	.000	.691	1.000
	Trust	59.571	1	59.571	120.992	.000	.834	1.000
	Recommendation acceptance	2.382	1	2.382	92.415	.000	.794	1.000
Task familiarity	Use	.848	1	.848	.856	.364	.034	.233
	Trust	.558	1	.558	1.134	.298	.045	.275
	Recommendation acceptance	.035	1	.035	1.373	.253	.054	.309
Accuracy	Use	9.666	1	9.666	9.764	.005	.289	.918
	Trust	25.758	1	25.758	52.315	.000	.686	1.000
	Recommendation acceptance	.036	1	.036	1.411	.247	.056	.314
Error	Use	23.759	24	.990				
	Trust	11.816	24	.492				
	Recommendation acceptance	.619	24	.026				
Total	Use	440.938	27					
	Trust	475.102	27					
	Recommendation acceptance	12.160	27					
Corrected Total	Use	34.546	26					
	Trust	38.519	26					
	Recommendation acceptance	.687	26					

The first main finding relates to the development of complacency. Figures 3(a) and 3(b) indicate that participants in either accuracy condition spent less time and attention examining the decision aid as they progressed through the five trials. As Table 2 shows, participants in the high-accuracy condition seem to have continuously and increasingly relied on the decision aid's recommendation, which indicates complacency. On the other hand, the relatively early sharp decline in the participants' agreement with the decision aid in the low-accuracy condition suggests that they might have noticed the inaccuracy initially and began questioning or not relying on the decision aid. Nevertheless, the following steep incline in their agreement indicates that the participants in the low-accuracy condition began to adopt the decision aid's recommendations despite the evidence that they realized inaccuracies in the decision aid's recommendations. Even though our findings suggest that accuracy might have an impact on the rate of complacency development, it seems that participants in both conditions were prone to becoming complacent. In other words, inaccuracy seemed to have (only) a short-term effect on use that was easily reversed by subsequent accurate recommendations. This finding suggests that reliance on decision aids might be robust to inaccuracy when the only alternative is intense cognitive effort, such as manual calculations to estimate stock prices.

An alternative explanation for the decrease in view times is that the participants learned how to use the decision aid over time and spent less time viewing the information it presented as the number of usage trials increased because they became more competent in using the decision aid and locating the relevant information (i.e., learning effects). Although we cannot entirely rule out the effects of learning, we believe that the decrease in view times can be attributed primarily to the development of complacency rather than learning effects for three main reasons. First, we instructed and trained the participants on how to use the decision aid before the experiment started. Therefore, we believe it is not likely that the participants' view times decreased as a result of learning how to use the decision aid over time because they were already familiar with the aid before the experiment began. Second, even though the decision aid layout remained the same, we provided the participants with different information content for each trial (such as different headlines and comments that they had to consider rather than with closing prices that they could compare), which is a common procedure for reducing the possibility of learning effects (e.g., Adipat, Zhang, & Zhou, 2011; Djamasbi et al., 2012). Third, attributing the decrease in view times to learning effects assumes that the participants learned how to use the decision aid to evaluate stocks faster over time. However, as Figure 3 shows, we observed that the participants spent an estimated average of eight seconds viewing the decision aid area and roughly 25 seconds viewing the raw information area for the final task. We argue that it is unlikely participants evaluated the stocks' performance and the decision aid's recommendation in such a short period of time considering the string of cognitive activities that needed to occur if they relied on the information provided rather than the decision aid's recommendation.

To make an informed decision or assess the aid's recommendation, the participants first had to incorporate the monthly closing prices for the past seven years, four recent headlines, three analyst comments, monthly estimated closing prices for the next year, and three bases for the decision aid's recommendation into their knowledge structures and then evaluate the usefulness and weight of each piece of information. Considering the unlikelihood that the participants evaluated, weighed, and verified all of these pieces of information in roughly 30 seconds, we believe that the participants could only have taken a heuristic approach to making their decisions based primarily on the decision aid's recommendation without spending enough time to verify it against the raw information. Thus, accompanied by the participants' increasing reliance on the decision aid's recommendations over time (as Table 2 shows), we believe that the decrease in view times can be attributed to a decrease in participants' verification efforts due to complacency rather than their becoming proficient in using the decision aid. Nevertheless, we cannot completely discount the possibility that learning effects played a role in the reduction of verification efforts and in the increase of recommendation acceptance. We further discuss this possibility as a limitation that future research can address toward the end of the paper.

All in all, it seems possible for complacency to develop regardless of accuracy, which further suggests that system 1 might be more influential on repeated or continuous technology use than many theoretical models indicate. The heat maps generated based on the eye tracker data (Figure 4) help explain this process. Recall that we observed that decision aid view time and fixation count declined across trials regardless of accuracy. To better comprehend the process, we display two sets of maps: one for the participants who worked in the high-accuracy condition and another for those that worked in the low-accuracy condition. In the high-accuracy condition, participants displayed a fairly steady decrease in the amount of attention given to the information provided with the decision aid (see the areas that present the recommendation basis and the predicted stock prices) and the raw information (see the areas that display stock prices, recent headlines, and analyst comments). Note that the attention paid to the actual recommendation remains fairly stable throughout the trials. In the low-accuracy condition, the development of complacency is still apparent although perhaps somewhat limited due to the inaccurate recommendations.

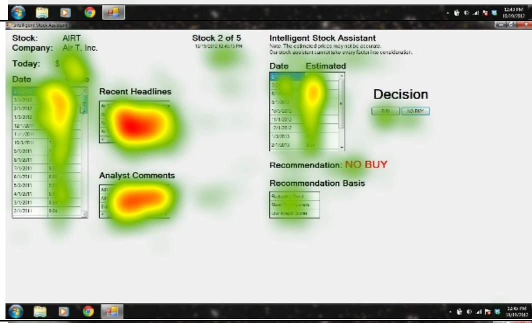
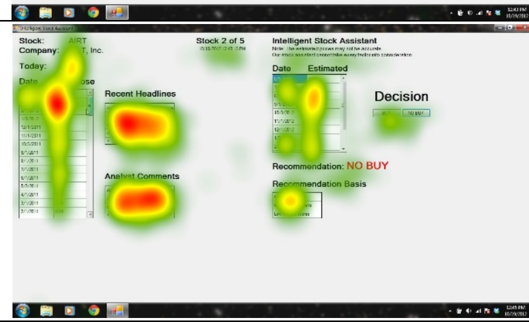
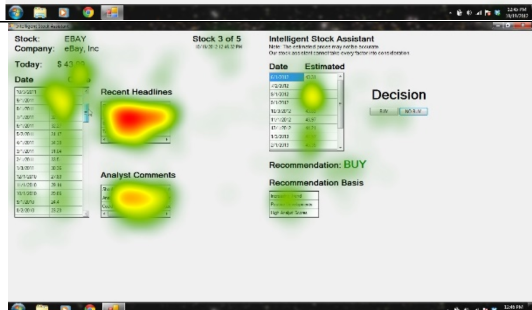
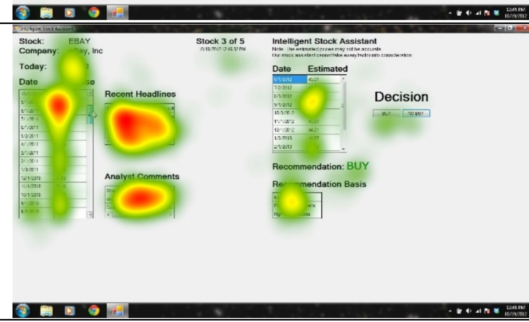
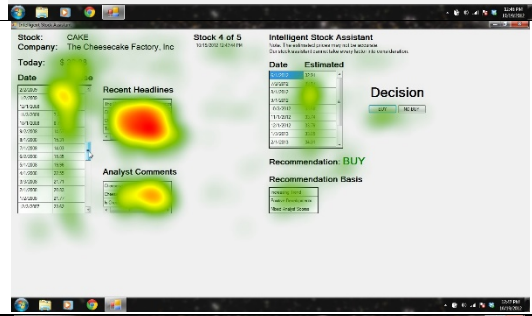
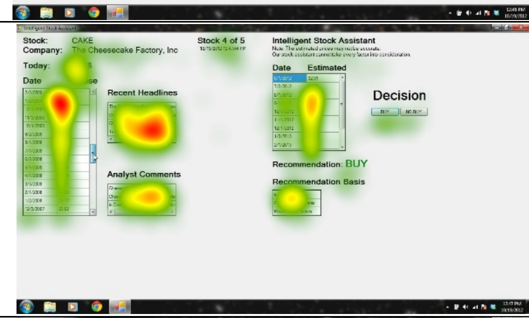
Trials	High-Accuracy Condition	Low-Accuracy Condition
Trial 1		
Trial 2		
Trial 3		
Trial 4		
Trial 5		

Figure 4. Heat Maps by Accuracy Condition

Another finding of this study reveals that complacency can develop rather quickly. Even though we only ran five trials, relatively few compared to an organizational setting, we clearly observed complacency's development. One possible explanation for this finding is that task complexity facilitates complacency, which is consistent with the cognitive-miser hypothesis of automation bias (Hollands & Wickens, 1999) that argues that human decision makers have a tendency to choose the path of least cognitive effort and, therefore, will be more likely to base complex decisions on decision aid recommendations rather than all other available information (Parasuraman & Manzey, 2010). The present experimental task (i.e., stock purchasing) is a fairly complex task with many inputs to the valuation (i.e., previous closing prices, recent headlines, and analyst comments). The complacency that we observed developing could be the result of the difficulty of the task, the number of inputs that participants had to review, and/or the unclear decision model of the decision aid (i.e., the weights applied to the different input variables). More research is required to better understand the extent to which task complexity promotes the development of complacency.

Our third finding indicates that complacency may have two main components. Our results suggest a dichotomy in the rise of complacency, and this insight comes from the way we captured it using an eye tracker. As time progresses, participants paid less attention to the decision aid (Figures 3(a) and 3(b)). This suggests that familiarity, which is a function of time, is the precipitating factor that leads to a decrease in scrutiny of the decision aid. However, our data suggest that a combination of time and accuracy were required to affect the attention participants paid to the raw information used to develop the recommendations (i.e., efforts to verify the aids' recommendation). Therefore, high accuracy *and* repeated usage of the decision aid may be necessary to reduce participants' verification efforts. This finding is consistent with the suggestion that users who are repeatedly exposed to a highly reliable decision aid will be more likely to engage in automatic or mindless usage behaviors (Parasuraman & Manzey, 2010). More research is necessary to investigate this dichotomy in complacency, but our results demonstrate that different factors influence the scrutiny of the decision aid and the verification of the decision's recommendations.

Finally, and perhaps most notably, our findings address the intentionality of IT use, a critical assumption made in much past MIS research. Our results point to a discrepancy between objective and subjective measures of decision aid use. Although participants reported different levels of trust and use between the high-accuracy and low-accuracy conditions, they did not differ significantly in terms of their actual reliance on the decision aid (as measured by their average agreement with the decision aid). Nor did they differ with regard to the time and attention spent on the decision aid (as evidenced by the view times and fixation counts). This finding indicates that mostly system 1 was driving participants' use of the decision aid in this study and supports the argument that individuals may not always be fully aware of how or how much they use technology (Ortiz de Guinea & Markus, 2009). Moreover, participants' trust in the decision aid was strongly associated with their self-reported use and continuance intentions, whereas we didn't find their trust to be associated with the participants' actual reliance on the decision aid. Taken together, these results imply that, while trust may be strongly influential on individuals' intentions to use technology, it may not be as powerful in driving the actual use or continuance of technology, which Lee and Moray (2004) suggest. In particular, when one examines the relationship between trust and use, it seems that there is more to the story when we look at actual use behaviors rather than only self-reported measures (e.g., use or usage intentions).

8. Implications

This study contributes to the literature in at least three ways. First, it improves our understanding of the use of decision aids and provides empirical support for the argument that IT use is less intentional and more automatic than previously assumed (Ortiz de Guinea & Markus, 2009). In doing so, it also suggests that the relationships between use and its antecedents (e.g., trust or accuracy) might be weaker than traditionally assumed by studies based on self-reported data. This is a theoretical contribution to the literature because our findings highlight the automatic nature of technology use and shows that the traditional assumption of rational and mindful technology use might not always hold. Second, this study helps us better understand how complacency develops, even without the previously suggested prerequisite that the decision aid being mostly reliable (Parasuraman, Sheridan, & Wickens, 2000). Finally, the results of this study yield important insights into the use and misuse of decision aids, including practical implications regarding user training and the design of decision aids.

Our observation that individuals may rely on decision aids even after realizing that the aid is faulty raises a significant concern about using decision aids in critical contexts. Based on our findings, we suggest that users of decision aids be warned and/or trained about complacency, especially in critical contexts where it cannot be tolerated. When system 1 is driving the use of a decision aid, it is easy for users to ignore important and relevant red flags such as inaccurate recommendations and continue to rely on the decision aid. While realizing inaccuracies might not be enough to activate system 2, training users to carefully scrutinize their "gut feelings" and to recognize when they are in a "cognitive minefield" can help them successfully overcome such complacency by willfully activating system 2 (Kahneman, 2011).

To assist individuals in building appropriate behaviors about using and operating decision aids, we also suggest that users should be exposed to boundary events where the accuracy of the decision aid may degrade unbeknownst to them. Even though this approach might appear undesirable at first, it may be more fruitful than simply warning users about the potential for inaccuracy, which, we observed, did not help much with preventing complacency. Previous research suggests that exposing users to rare false recommendations can be a successful countermeasure for complacency even though it cannot be completely prevented this way (Bahner et al., 2008). Combined with proper training, such intentional false recommendations can help maximize users' verification efforts and potentially minimize complacency.

Besides focusing on users, it could also be possible to mitigate complacency via designing decision aids aimed at keeping users aware of their reliance on the decision aid. This could be done by developing feedback mechanisms that inform users about their verification efforts and progressive reliance on the decision aids' recommendations. For instance, warning users about immediate agreement with the decision aid or about significant and consistent decreases in the time they take to make consecutive decisions may be beneficial. Since system 2 often endorses ideas and feelings generated by system 1, it is difficult for individuals to distinguish between elaborated and heuristic-based decisions (Kahneman, 2011). Such external warnings about their behaviors could help users realize that system 1 is driving their decision making process and encourage them to willfully engage system 2 to override complacency. Alternatively, the recommendations of the decision aid could be periodically turned off for pre-defined non-critical tasks, which would force the activation of system 2 because users would have to make their own decisions based on the raw information available. This could help keep the users relatively more active in the decision making process and aid in mitigating their over-reliance on the decision aid. We call for future research to explore how effective such measures are for the mitigation of complacency.

9. Limitations and Future Research

One inherent limitation of our exploratory study is the small sample size and, hence, the marginal statistical significance of some of our results. Although similar sample sizes are common among past studies using similar methodologies, a larger sample size would provide a more stringent test of the pattern of behaviors we observed and predicted. Furthermore, the context of the decision making problem might play an important role in the development of complacency and intentionality. Thus, it would be beneficial for future researchers to replicate, confirm, and expand our exploratory findings in additional decision making contexts and perhaps with professional users of decision aids, such as professional stockbrokers.

In this study, we assumed a direct relationship between accuracy and complacency, consistent with previous research (e.g., Molloy & Parasuraman, 1996; Parasuraman et al., 1993). However, there are several cognitive processes and mechanisms through which accuracy can indirectly influence complacency, such as habit and trust formation or carelessness (i.e., decrease in attention). We call for future research to investigate and distinguish between the mechanisms through which accuracy can impact complacency to further improve our understanding of complacency and how to mitigate it.

Even though we observed complacency develop regardless of accuracy, modifications to our experimental design could allow researchers to investigate effects of different elements of inaccuracy on its development. For instance, it is possible that the timing (i.e., early vs. late), frequency (i.e., rare vs. often), and magnitude (i.e., small vs. large) of the inaccuracy of recommendations could impact how likely or how quickly a user is to become complacent. Future studies could examine how such factors affect users' reliance on a decision aid, intentionality, and complacency.

As we previously note, we cannot entirely rule out the possibility of learning effects as an alternative explanation for the decrease in participants' verification efforts accompanied by their increasing reliance on the decision aid's recommendations. Future research could address this limitation by confirming our findings regarding complacency in other contexts. Potential learning effects could also be minimized through experimental design by conducting a much longer training phase and/or by randomizing the experimental task order plus the timing, frequency, and magnitude of recommendation errors between participants.

Another avenue for future research, which we point out earlier, is studying how to avoid or mitigate complacency either through the design of decision aids or the training of their users. The findings of such research can help us better understand individuals' attitude towards and interaction with decision aids and improve their decision quality.

Finally, the findings of this study point towards the necessity of validating or revising previous theoretical models developed on studies involving only self-reported usage or use intention data. Future studies on other potentially automatic or mindless processes similar to technology use/continuance, such as technology acceptance or resistance, could also benefit from using objective data.

10. Conclusion

Decision aids improve the effectiveness of decision making beyond a level that humans alone can reach; however, most can occasionally offer incorrect recommendations. Many recent anecdotes point to the dangers of relying on recommendations of decision aids in an automatic and complacent manner. In this study, we investigated the development of complacency and intentionality in decision aid use. Our results support the arguments that technology use might not be as intentional as traditionally assumed and that complacency can develop regardless of the accuracy of the decision aid. These findings have important implications for HCI, MIS, and DSS researchers and for practitioners who design or frequently rely on decision aids. We call for future research to build on our findings and explore further the antecedents and consequences of complacency and intentionality in technology use.

Appendix A. Survey Items (Answered on a 1-7 Scale)

1. Use/continuance (adapted from Hayes, 2006):

A. To what extent did you use this decision aid to make a buy/no-buy decision?

(1—not at all; 7—a lot)

B. To what extend did you rely on the recommendation of this decision aid in making your final buying decision?

(1—not at all; 7—a lot)

C. If available in the future, how likely are you to use this decision aid to make a stock purchasing decision?

(1—very unlikely; 7—very likely)

D. If available in the future, how likely are you to rely on the recommendation of this decision aid in making your final buying decision?

(1—very unlikely; 7—very likely)

2. Trust (adapted from Jian et al., 2000):

A. The decision aid is deceptive.

(1—not at all; 7—extremely)

B. The decision aid behaves in an underhanded manner.

(1—not at all; 7—extremely)

C. I am suspicious of the decision aid's recommendation.

(1—not at all; 7—extremely)

D. I am confident in the decision aid.

(1—not at all; 7—extremely)

E. The decision aid is dependable.

(1—not at all; 7—extremely)

F. The decision aid is reliable.

(1—not at all; 7—extremely)

G. I can trust the decision aid.

(1—not at all; 7—extremely)

3. Task familiarity (adapted from Adams, 2010):

A. How familiar are you with buying stocks?

(1—not very familiar; 7—very familiar)

B. How frequently do you buy stocks?

(1—never; 7—very often)

Appendix B. Results of Repeated ANCOVAs

Table B-1. Raw Information View Time—Within-Subject Effects[1]

Source	Type III sum of squares	Df	Mean square	F	Sig.	Partial eta squared	Observed power
Trial	1103.058	3.541	311.523	1.576	.194	.059	.571
Trial * task familiarity	478.555	3.541	135.152	.684	.588	.027	.311
Trial * accuracy	1601.067	3.541	452.169	2.287	.074	.084	.727
Error (trial)	17501.900	88.521	197.714				

[1] Huynh-Feldt corrected scores are reported since the sphericity assumption was violated (Mauchly's W = 0.431, $p < 0.020$).

Table B-2. Raw Information View Time—Between-Subject Effects

Source	Type III sum of squares	Df	Mean square	F	Sig.	Partial eta squared	Observed power
Intercept	18198.408	1	18198.408	12.529	.002	.334	.964
Task familiarity	646.259	1	646.259	.445	.511	.017	.171
Accuracy	2.624	1	2.624	.002	.966	.000	.100
Error	36313.898	25	1452.556				

Table B-3. Raw Information Fixation Count—Within-Subject Effects[1]

Source	Type III sum of squares	Df	Mean square	F	Sig.	Partial eta squared	Observed power
Trial	9979.839	3.792	2631.917	1.775	.144	.066	.638
Trial * task familiarity	5023.812	3.792	1324.896	.894	.467	.035	.387
Trial * accuracy	6839.512	3.792	1803.739	1.217	.309	.046	.488
Error (trial)	140541.243	94.796	1482.560				

[1] We report Huynh-Feldt corrected scores since the sphericity assumption was violated (Mauchly's W = 0.485, $p < 0.050$).

Table B-4. Raw Information Fixation Count—Between-Subject Effects

Source	Type III sum of squares	Df	Mean square	F	Sig.	Partial eta squared	Observed power
Intercept	175463.648	1	175463.648	18.555	.000	.426	.994
Task familiarity	4361.789	1	4361.789	.461	.503	.018	.173
Accuracy	51.181	1	51.181	.005	.942	.000	.101
Error	236410.285	25	9456.411				

Table B-5. Decision Aid View Time—Within-Subject Effects[1]							
Source	**Type III sum of squares**	**Df**	**Mean square**	**F**	**Sig.**	**Partial eta squared**	**Observed power**
Trial	435.440	4	108.860	2.070	.090	.076	.719
Trial * task familiarity	230.208	4	57.552	1.094	.364	.042	.461
Trial * accuracy	292.832	4	73.208	1.392	.242	.053	.551
Error (trial)	5258.576	100	52.586				

[1] The sphericity assumption was not violated (Mauchly's W = 0.660, p < 0.374).

Table B-6. Decision Aid View Time—Between-Subject Effects							
Source	**Type III sum of squares**	**Df**	**Mean Square**	**F**	**Sig.**	**Partial eta squared**	**Observed power**
Intercept	1468.798	1	1468.798	16.734	.000	.401	.990
Task familiarity	107.908	1	107.908	1.229	.278	.047	.289
Accuracy	5.958	1	5.958	.068	.797	.003	.111
Error	2194.323	25	87.773				

Table B-7. Decision Aid Fixation Count—Within-Subject Effects[1]							
Source	**Type III sum of squares**	**Df**	**Mean square**	**F**	**Sig.**	**Partial eta squared**	**Observed power**
Trial	4250.643	4	1062.661	2.101	.086	.078	.725
Trial * task familiarity	1848.279	4	462.070	.914	.459	.035	.403
Trial * accuracy	3930.831	4	982.708	1.943	.109	.072	.691
Error (trial)	50580.605	100	505.806				

[1] The sphericity assumption was not violated (Mauchly's W = 0.661, p < 0.378).

Table B-8. Decision Aid Fixation Count—Between-Subject Effects							
Source	**Type III sum of squares**	**Df**	**Mean square**	**F**	**Sig.**	**Partial eta squared**	**Observed power**
Intercept	20892.837	1	20892.837	24.030	.000	.490	.999
Task familiarity	807.776	1	807.776	.929	.344	.036	.245
Accuracy	13.106	1	13.106	.015	.903	.001	.102
Error	21736.325	25	869.453				

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